Sequence Labelling and Part-of-Speech Tagging

COM4513/6513 Natural Language Processing

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The University Of Sheffield.

In the previous lecture...

- Our first **sequence modelling** problem: **Language Modelling**

In this lecture...

- What about if we want to **assign a label to each word in a sequence**?

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- Sequence labelling!

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- What about if we want to **assign a label to each word in a sequence**?
- Sequence labelling!
- Applications?

Applications

- Part-of-Speech (POS) Tagging

$$(\mathbf{x}, \mathbf{y}) = ([I, studied, in, Sheffield], \\ [Pronoun, Verb, Preposition, ProperNoun])$$

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&[Pronoun, Verb, Preposition, ProperNoun])
\end{aligned}
$$

- Named Entity Recognition

$$
\begin{aligned}
(\mathbf{x}, \mathbf{y}) = ([&Giannis, Antetokounmpo, plays, for, the, Bucks], \\
&[Person, Person, NotEnt, NotEnt, NotEnt, Org])
\end{aligned}
$$

- Machine Translation (reconstruct word alignments)

$$
\begin{aligned}
(\mathbf{x}, \mathbf{y}) = ([&la, maison, bleu], \\
&[the, house, blue])
\end{aligned}
$$

We will use POS tagging as a running example

Parts of Speech (POS)

Label words according to their syntactic function in a sentence:

The	results	appear	in	today	's	news
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What could they be useful for?

- text classification
- language modelling
- syntactic parsing
- named entity recognition
- question answering

PoS Tags

- Open class:
  nouns, verbs, adjevtives
- Closed class:
  determiners, prepositions, conjunctions, etc

PoS definitions

- Most research uses the Penn Treebank PoS tag set
- Includes 45 tags making distinctions between:
  - verbs in active vs past tense
  - nouns in singular vs plural number
  - etc.

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  - etc.
- Penn Tree Bank inspired by English. Recent work has focused on the Universal PoS tag set:
  - 17 coarse tags: one noun class, one verb class, etc.
  - developed considering 22 languages

Sequence labelling: Problem Setup

Data consists of word sequences with label sequences:

$$
\begin{aligned}
D_{train} &= \{(\mathbf{x}^1, \mathbf{y}^1)...(\mathbf{x}^M, \mathbf{y}^M)\} \\
\mathbf{x}^m &= [x_1, ...x_N] \\
\mathbf{y}^m &= [y_1, ...y_N]
\end{aligned}
$$

Learn a model f that predicts the best label sequence:

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}} f(\mathbf{x}, \mathbf{y}) \tag{1}$$

$\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}$ is the set of all possible combinations of label sequences and $\mathcal{Y} = \{A, B, C...\}$ are the possible classes for each word.

Could we use a dictionary-based model?

$$\{`the' : `determiner', `can' : `modal', `fly' : `verb'\}$$

Could we use a dictionary-based model?

$$\{\text{`}the' : \text{`}determiner', \text{`}can' : \text{`}modal', \text{`}fly' : \text{`}verb'\}$$

Yes, but the same word can have different tags in different contexts.

I	can	fly
pronoun	modal	verb

vs:

I	can	fly
pronoun	verb	noun

can and 11.5% of the words in the Brown corpus have more than one tag

Can we use a Markov model?

Use tags **y** instead of words:

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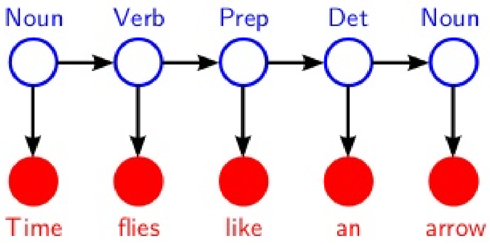
What about the words? We will get whe same N-tag long sequence for any sentence!

Hidden Markov Model (HMM)



- Labels y_i (i.e. PoS tags) are hidden states emitting words.
- Assumptions:
  - 1st order Markov among the POS tags (current tag depends only on previous tag)
  - Each word only depends on its POS tag

HMM: Derivation

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}} P(\mathbf{y}|\mathbf{x}) \quad \text{(Bayes rule)}$$

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$$\hat{\mathbf{y}} \approx \arg\max_{\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}} \prod_{n=1}^{N} P(x_n|y_n)P(y_n|y_{n-1})$$

HMM: Training

- Maximum likelihood estimation (i.e. counts!):

  $P(y_n|y_{n-1}) = \frac{c(y_n, y_{n-1})}{c(y_{n-1})}$ (transition probabilities)

  $P(x_n|y_n) = \frac{c(x_n, y_n)}{c(y_n)}$ (emission probabilities)

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- We can easily compute counts $c(\cdot)$ using a labelled corpus (pairs of words-POS tags).

HMM: Example

x = [START, I, can, fly, END]
y = [START, PPSS, MD, NN, END]

$$
\begin{aligned}
P(\mathbf{y}|\mathbf{x}) = & P(I|PPSS)P(PPSS|START) \\
& P(can|MD)P(MD|PPSS) \\
& P(fly|NN)P(NN|MD)
\end{aligned}
$$

Decoding/Inference

- So we have everything we need to decode/infer the most likely tag sequence for a sentence:

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- We will see later how to decode efficiently!

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- Smoothing:
  - what happens when we have unseen word/tags or tag-tag combinations?
    Use methods we learned in the language modeling lecture!

HMMs: Limitations

- They generate probabilities for words and labels, we just want labels
- No overlapping features (e.g. unigrams+bigrams)
- No subword features (e.g. suffixes)

Conditional Random Fields: Extend LR for Sequence Labelling

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Conditional Random Fields: Extend LR for Sequence Labelling

- Logistic regression can also provide probabilities but supports more flexible representations!
- Given a word, a candidate label of the current and the label of the previous word, predict the most likely label for that word using a (multi-class LR) in each time step $\rightarrow$ Conditional Random Fields
- CRF paper more than 11K citations since 2001, 10 year test of time award at ICML conference

Conditional Random Fields

Decompose the per sentence $\mathbf{x} = [x_1, ...x_N]$ prediction:

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}} f(\mathbf{x}, \mathbf{y})$$

into each word x_n:

$$\hat{y}_n = \arg\max_{y \in \mathcal{Y}} f(x_n; y_{n-1}, n) = \arg\max_{y \in \mathcal{Y}} \mathbf{w}^y \phi(x_n, y_{n-1}, n)$$

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- How to construct a feature vector $\phi(x_n, y_n, y_{n-1}, n)$?

CRF: Feature Vectors

- $\phi_1(x_n, y_n, y_{n-1}, n) = 1$ if $y_n = ADVERB$ and the n-th word ends in "-ly"; 0 otherwise.
  "usually","casually"
- $\phi_2(x_n, y_n, y_{n-1}, n) = 1$ if $n = 1$, $y_n = VERB$, and the sentence ends in a question mark; 0 otherwise.
  "Is it true?"
- etc.

CRF: Inference

The normalisation factor has to score all possible label sequences for all sentences, so it is ignored:

$$\arg\max_{\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}} P_{CRF}(\mathbf{y}|\mathbf{x};\mathbf{w}) = \arg\max_{\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}} \sum_{n=1}^{N} \mathbf{w} \cdot \phi(y_n, y_{n-1}, \mathbf{x}, n)$$

CRF: Training

- Training by minimising the negative log-likelihood objective:

$$\mathbf{w} = \underset{\mathbf{w} \in \Re^d}{\arg\min} \sum_{m=1}^{M} -\log P_{CRF}(\mathbf{y^m} | \mathbf{x^m}; \mathbf{w})$$

- using **Stochastic Gradient Descent**

Decoding with Viterbi

- Enumerating all possible tag sequences in HMM and CRF is intractable!

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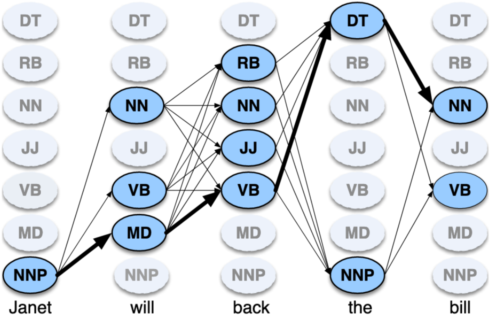
- Enumerating all possible tag sequences in HMM and CRF is intractable!
- Dynamic programming: store and re-use calculations
- Possible due to independence assumptions
- Keep track of the highest probability to reach each PoS tag for each word and how we got there

Decoding with Viterbi



Viterbi: Data structures

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Viterbi: Data structures

- **Viterbi score matrix** $V^{|\mathcal{Y}| \times N}$:
  - Tag set $\mathcal{Y}$, sentence $\mathbf{x} = [x_1, ...x_N]$
  - each cell contains the highest prob. for word n with tag y
  - 1st order Markov: only depends on the previous tag y_{n-1}
    $V[y, n] = \max_{y_{n-1} \in \mathcal{Y}} V[y_{n-1}, n-1] \times P(y_n | x_n, y_{n-1})$

Viterbi: Data structures

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Viterbi: Data structures

- **Backpointer matrix** $backptr^{|\mathcal{Y}| \times N}$:
  - instead of the max score, keep the previous tag that got it
  - *argmax* instead of *max*
    $backptr[y, n] = \arg\max_{y' \in \mathcal{Y}} V[y', n-1] \times P(y|y') \times P(x_n|y)$

Viterbi algorithm

Input: *word sequence* $\mathbf{x} = [x_1, ..., x_N]$,

$P(y_n | x_n, y_{n-1})$ *probs*

set matrix $V^{|\mathcal{Y}| \times N} = 1$

for $n = 1$ **to** N **do**

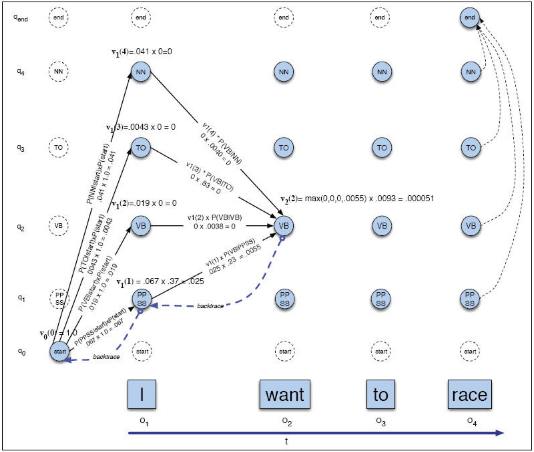
  for $y \in \mathcal{Y}$ **do**

$$V[y, n] = \max_{y_{n-1} \in \mathcal{Y}} V[y_{n-1}, n-1] \times P(y_n | x_n, y_{n-1})$$

$$backptr[y, n] = \arg\max_{y_{n-1} \in \mathcal{Y}} V[y_{n-1}, n-1] \times P(y_n | x_n, y_{n-1})$$

$$backptr[None, N+1] = \arg\max_{y_{n-1} \in \mathcal{Y}} V[y_{n-1}, N] \times P(None | y_{n-1})$$

Viterbi diagram



Break the large arg max into smaller ones, left-to-right (**dynamic programming**)

Beam Search: Inexact Decoding

- Viterbi performs exact search (under assumptions) by evaluating all options.

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- Viterbi performs exact search (under assumptions) by evaluating all options.
- Get faster by being inexact, i.e. avoid labelling some candidate sequences with **Beam Search**

Beam Search

- Do Viterbi, but keep only best k hypotheses at each step

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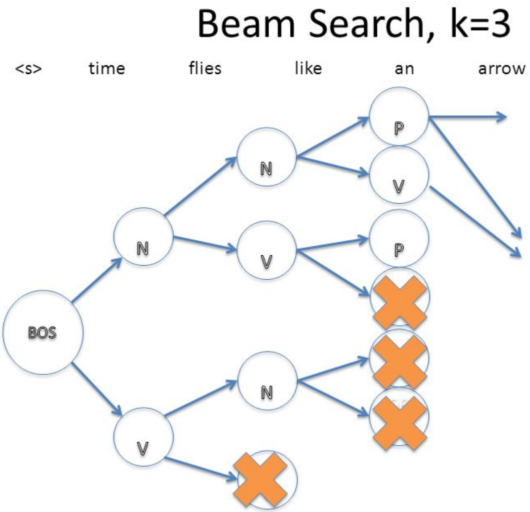
- If beam size is 1, then we have greedy search
- Often beams less than 10 get close to exact search, but much faster
- Beams must be of the same length to be comparable
- Attractive when we need complex feature functions i.e. avoid Markov assumptions)

Beam Search: Example



Beam Search: Algorithm

Input: *word sequence* $\mathbf{x} = [x_1, ..., x_N]$, *weights* $\mathbf{w}$

set beam $B = \{(\mathbf{y_{temp}} = [START], score = 0)\}$, *size* k

for $n = 1$ **to** N **do**

  $B' = \{\}$

  for $b \in B$ **do**

    for $y \in \mathcal{Y}$ **do**

      $B' = B' \cup ([b.\mathbf{y_{temp}}; y], P([b.\mathbf{y_{temp}}; y]|x_n))$

  $B = \text{TOP-k}(B')$

return $\text{TOP-1}(B)$

Bibliography

- Chapter 8 from Jurafsky and Martin
- Sections 7.1-7.4 and 7.5.3 from Eisenstein
- This blog post on CRFs by Edwin Chen
- Tutorial on CRFs by Sutton and McCallum

Coming up next...

The best-studied, more complex than sequence labeling problem in NLP: **dependency parsing**